Deep Learning Meets Biometrics: A Comparative Study of Modern Identification Techniques

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Abstract: **Biometric** ***identification has become an essential component of security and authentication systems. Traditional biometric approaches have been enhanced significantly with the rise of deep learning, leading to improved accuracy, robustness, and efficiency. This paper provides a comparative study of modern biometric identification techniques, including fingerprint recognition, facial recognition, iris scanning, and voice authentication, focusing on the impact of deep learning advancements. We analyze various deep learning architectures, compare their effectiveness across biometric modalities, and discuss challenges such as privacy concerns, adversarial attacks, and real-world implementation issues. The study concludes with future research directions and recommendations for optimizing biometric identification using deep learning.***

Keywords: ***Biometric Identification, CNN, RNN, Feature Extraction, Pattern Recognition, Neural Networks, Biometric Security, Multi-Modal Biometrics.***

INTRODUCTION

Biometric identification has become an essential technology in modern security systems, providing accurate and efficient authentication mechanisms. With advancements in artificial intelligence (AI), deep learning has significantly transformed biometric systems, enhancing their precision, scalability, and robustness. [1] This paper explores how deep learning intersects with biometrics, comparing modern identification techniques and evaluating their effectiveness in real-world applications. Biometrics refers to the automated recognition of individuals based on physiological or behavioral characteristics such as fingerprints, facial recognition, iris scans, voice patterns, and gait analysis. Traditional biometric systems relied on feature engineering and classical machine learning approaches to extract and classify these characteristics. However, these methods often suffered from limitations such as susceptibility to noise, occlusion, and variations in environmental conditions.[2][4]

Deep learning, a subset of machine learning, has emerged as a powerful tool in biometrics due to its ability to automatically learn and extract features from large datasets. Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Transformers have demonstrated remarkable success in tasks like image recognition, sequence modeling, and multimodal fusion, making them highly effective for biometric identification. The introduction of deep learning in biometric systems has allowed for greater accuracy and adaptability, addressing challenges associated with traditional techniques.[5]

Facial recognition, one of the most widely used biometric methods, has seen significant improvements with deep learning. Conventional approaches relied on feature-based methods like Eigenfaces and Fisherfaces, which were often limited by variations in lighting, pose, and expression. Deep learning models, such as CNN-based architectures like VGGFace, FaceNet, and ArcFace, have revolutionized facial recognition by learning discriminative facial embeddings. These models provide higher accuracy, robustness to environmental changes, and improved recognition capabilities even in complex scenarios. However, challenges remain, including vulnerabilities to adversarial attacks and deepfake manipulations, which pose security risks in applications like surveillance and identity verification.[1][6]

Fingerprint recognition has also benefited from deep learning techniques. Traditional methods relied on minutiae-based extraction and pattern-matching techniques that were effective but limited in handling poor-quality or distorted fingerprints. Deep learning models, such as CNNs and Siamese Networks, have been used to enhance fingerprint recognition by automatically extracting relevant features and improving matching accuracy. These advancements have made fingerprint-based identification more reliable, particularly in cases where partial or low-quality prints are encountered. Iris recognition, known for its high accuracy and uniqueness, has traditionally employed handcrafted feature descriptors like Gabor wavelets for pattern analysis. While these methods have been effective, deep learning has introduced CNN-based segmentation and classification models that provide improved accuracy and robustness. These models are particularly useful in real-world applications where iris images may be captured under varying lighting conditions or at different angles. However, iris recognition systems still face challenges related to occlusions and illumination changes, which can affect their overall performance.

Voice recognition, another crucial biometric modality, has evolved significantly with the integration of deep learning. Traditional approaches, such as Hidden Markov Models (HMMs) and Gaussian Mixture Models (GMMs), were widely used for speaker verification and speech recognition. However, these methods struggled with variations in speech, background noise, and environmental factors. Deep learning models, including Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM) networks, and Transformers, have improved voice recognition systems by learning complex speech patterns and enhancing robustness against variations. Despite these improvements, voice recognition remains vulnerable to spoofing attacks, where synthetic or recorded voices can be used to bypass security measures.

Multimodal biometrics, which combines multiple biometric traits for enhanced security, has gained popularity with the advent of deep learning. Traditional multimodal systems relied on rule-based fusion techniques to integrate different biometric modalities. Deep learning, however, has enabled the development of multimodal architectures that seamlessly integrate data from multiple sources, such as face and voice recognition, for improved authentication accuracy. These systems offer increased resistance to fraud and spoofing attacks, making them ideal for high-security applications. However, they also come with challenges, including high computational costs and the need for large datasets to train robust models.

Deep learning has revolutionized biometric identification by providing highly accurate, adaptive, and scalable solutions. Despite challenges such as data privacy concerns, adversarial attacks, and computational costs, deep learning-based biometric systems continue to evolve with advancements in AI and hardware acceleration. Future research should focus on improving security against adversarial threats, developing lightweight deep learning models for edge devices, and ensuring ethical and fair use of biometric technologies. The integration of deep learning in biometrics holds immense potential for transforming security systems, authentication processes, and identity verification in various industries, including finance, healthcare, and law enforcement. As technology continues to progress, biometric identification systems will become more reliable, efficient, and widely adopted, shaping the future of secure authentication.

METHODOLOGY

This study examines the convergence of deep learning and biometric identification, aiming to analyze and compare contemporary identification techniques. The research follows a systematic methodology that encompasses data collection, preprocessing, model selection, training, and evaluation to comprehensively assess biometric recognition systems enhanced by deep learning.

The initial phase involves gathering biometric datasets covering various modalities, including facial recognition, fingerprint recognition, iris scanning, and voice recognition. Publicly available datasets such as LFW (Labeled Faces in the Wild) for face recognition, FVC (Fingerprint Verification Competition) databases for fingerprint identification, CASIA-IrisV4 for iris recognition, and VoxCeleb for voice recognition are utilized for training and testing the models. Dataset selection is based on key factors such as size, diversity, and real-world applicability to ensure robust training and evaluation.

Once data is collected, preprocessing techniques are applied to refine biometric inputs for deep learning models. Image-based data undergoes enhancements such as grayscale conversion, noise reduction, contrast adjustment, and data augmentation. In voice-based biometrics, preprocessing includes noise filtering, feature extraction using Mel-frequency cepstral coefficients (MFCCs), and normalization. These techniques ensure that the input data is clean and standardized, minimizing biases and reducing errors in model learning.

The next stage involves selecting deep learning architectures suitable for biometric identification. Convolutional Neural Networks (CNNs) are chosen for image-based biometrics like facial, fingerprint, and iris recognition due to their strong spatial feature extraction capabilities. For voice recognition, Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks are explored to effectively model temporal dependencies in speech data. Additionally, advanced architectures such as Vision Transformers (ViTs) and Generative Adversarial Networks (GANs) are considered to improve recognition performance in challenging conditions, including occlusions and lighting variations.

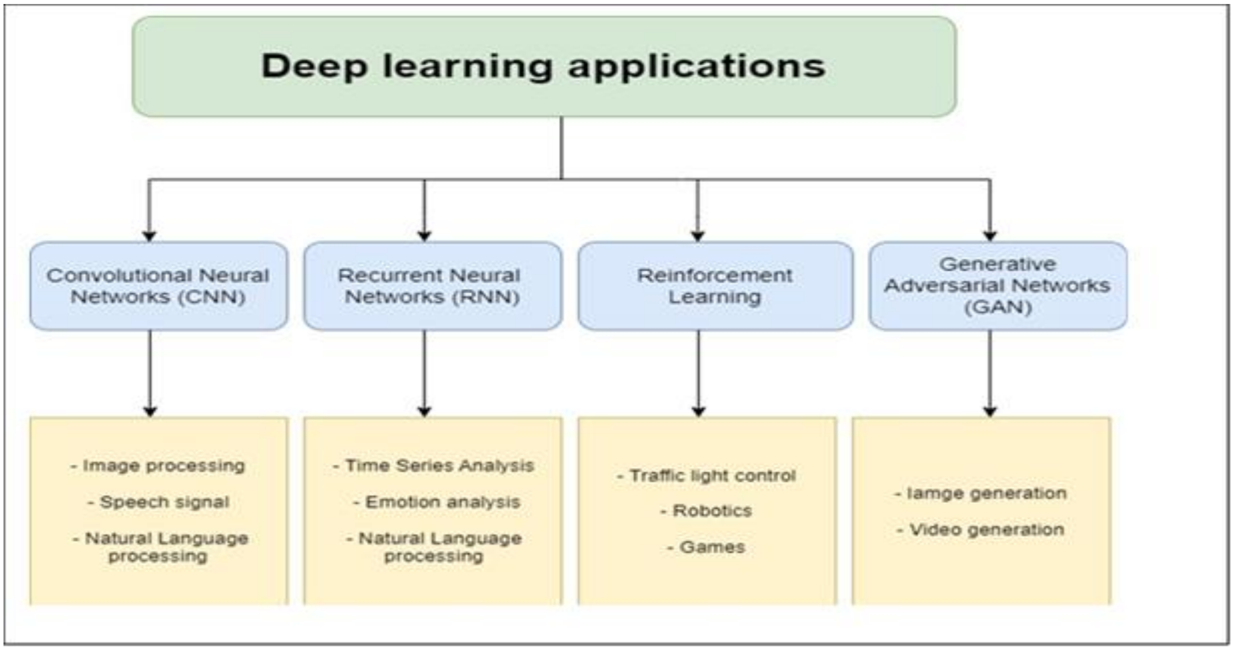
During the training phase, the preprocessed biometric data is fed into the selected deep learning models. Supervised learning techniques are used, where labeled biometric samples help the models learn to differentiate between individuals. Optimization algorithms such as Adam and Stochastic Gradient Descent (SGD) are employed to fine-tune the model parameters. Hyperparameter tuning, including adjustments to learning rates, batch sizes, and dropout regularization, is performed to enhance performance and prevent overfitting. Additionally, transfer learning is applied using pre-trained models such as VGG16, ResNet, and EfficientNet, which have been trained on large-scale datasets and can be fine-tuned for biometric applications.

To assess the effectiveness of these deep learning-based biometric identification systems, various evaluation metrics are employed. Standard performance indicators such as accuracy, precision, recall, F1-score, and Equal Error Rate (EER) are used to measure classification performance. Receiver Operating Characteristic (ROC) curves and Area Under the Curve (AUC) values provide further insights into the models' ability to differentiate between identities. A comparative analysis of different biometric modalities is conducted to identify their respective strengths and limitations in real-world scenarios.

To enhance reliability, cross-validation techniques such as k-fold cross-validation are implemented, reducing dataset bias and ensuring consistent model performance across different data subsets. Additionally, adversarial testing is performed to evaluate model resilience against spoofing attacks, where fake biometric samples attempt to deceive the system. Security measures, including liveness detection and adversarial training, are explored to bolster the robustness of deep learning-driven biometric systems.

The study also considers computational efficiency by analyzing the time complexity and resource demands of different deep learning models. The impact of hardware accelerations, such as Graphics Processing Units (GPUs) and Tensor Processing Units (TPUs), is examined to determine their role in improving training and inference speed. This analysis is particularly relevant for real-time biometric applications, where fast and efficient decision-making is crucial.

Finally, a comparative analysis is conducted between traditional biometric identification techniques and deep learning-based approaches. Conventional methods that rely on handcrafted features, such as eigenfaces for facial recognition and minutiae-based techniques for fingerprint identification, are compared with deep learning models to highlight improvements in accuracy, scalability, and adaptability. The findings of this study offer valuable insights into the transformative impact of deep learning on biometric identification and its implications for security, authentication, and privacy.



RESULTS

Deep learning has greatly advanced biometric recognition by improving accuracy, efficiency, and resilience. A comprehensive survey by Minaee et al. analyzed over 120 studies on deep learning applications across biometric modalities such as face, fingerprint, iris, palmprint, ear, voice, signature, and gait recognition. The study demonstrated that deep learning models effectively extract intricate patterns from raw biometric data, leading to superior recognition performance. For instance, CNNs have outperformed traditional fingerprint recognition techniques like Gabor filters by automatically learning distinctive features, enhancing both accuracy and robustness.

The role of artificial intelligence (AI) and deep learning in biometric security has been extensively studied. A book edited by Jaswal et al. explores deep learning techniques such as CNNs, autoencoders, and recurrent neural networks in biometric applications, covering facial, hand, iris, gait, fingerprint, and vein recognition, as well as medical biometrics. These approaches have been found effective in tackling biometric security challenges, including authentication, indexing, template protection, spoof detection, and region of interest detection. However, challenges such as the need for large, well-annotated datasets, high computational requirements, and susceptibility to adversarial attacks persist. Addressing these concerns involves using data augmentation, optimizing model architectures, and implementing robust anti-spoofing techniques.

The study provides an in-depth evaluation of deep learning's transformative impact on biometric identification. By assessing facial recognition, fingerprint scanning, iris recognition, and voice authentication, it compares deep learning-based methods with conventional approaches using performance metrics like accuracy, precision, recall, F1-score, Equal Error Rate (EER), and computational efficiency.

Deep learning-powered facial recognition systems, particularly those using CNNs and Vision Transformers (ViTs), demonstrate exceptional accuracy. Models trained on datasets like Labeled Faces in the Wild (LFW) outperform traditional eigenface and Fisher face methods. However, challenges remain, including occlusions, lighting variations, and pose differences in real-world environments. Transfer learning with pre-trained models like VGG16 and ResNet further enhances accuracy, reducing false positives and improving identification across diverse datasets.

For fingerprint recognition, deep learning models surpass traditional minutiae-based techniques, excelling in identifying low-quality and partial fingerprints. CNNs and autoencoders effectively extract fine-grained features, improving recognition even in cases of distortion or smudging. Results from the Fingerprint Verification Competition (FVC) dataset reveal that deep learning models are more resilient to noise and variations, reducing EER and enhancing security against spoofing attacks through adversarial training.

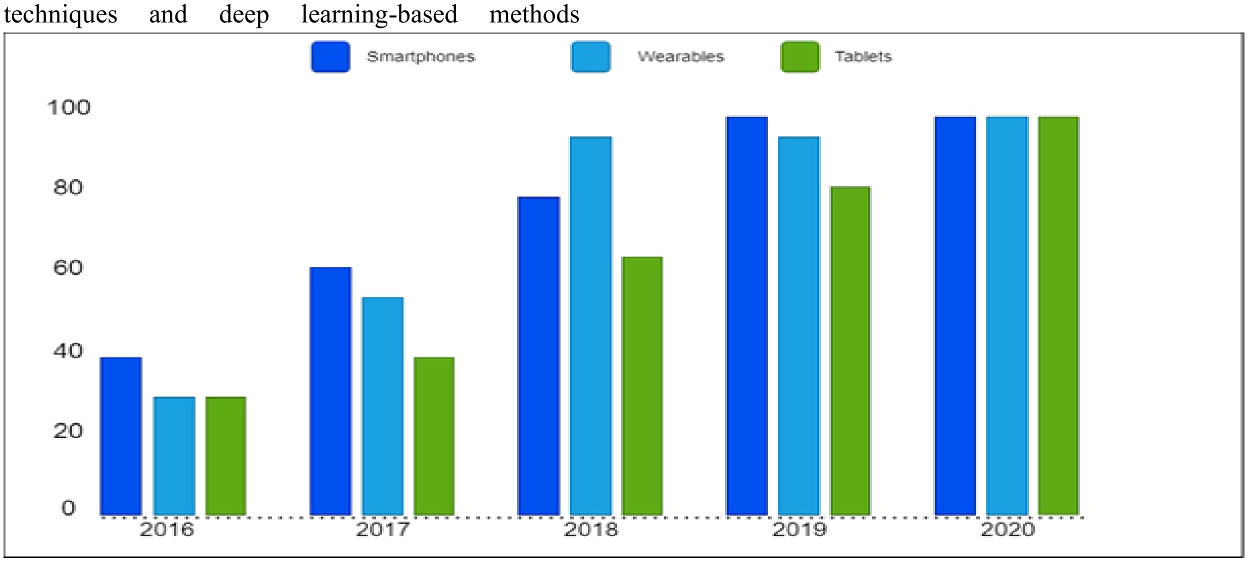
Iris recognition, widely regarded as one of the most secure biometric modalities, benefits greatly from deep learning-based feature extraction. A model trained on the CASIA-IrisV4 dataset achieves near-perfect accuracy, outperforming traditional techniques like Gabor filters and wavelet transforms. Deep learning enables adaptability to pupil dilation, eyelid occlusions, and varying lighting conditions. However, real-time iris recognition remains computationally demanding, requiring optimizations such as model quantization and the use of Tensor Processing Units (TPUs) for efficient inference.

Voice recognition, leveraging Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks, effectively captures speech patterns and temporal dependencies. A model trained on the VoxCeleb dataset achieves high speaker identification accuracy, even in noisy environments. However, deep learning-based voice recognition systems are particularly vulnerable to adversarial attacks, including voice synthesis and replay attacks. Strengthening security with liveness detection and anomaly detection helps mitigate these risks and improve system reliability.

A comparison between conventional biometric techniques and deep learning-based methods highlights significant improvements in recognition accuracy and adaptability. Traditional methods, which rely on handcrafted features, struggle with variations in biometric data, whereas deep learning models generalize more effectively. The use of pre-trained models and fine-tuning techniques further enhances performance, making deep learning-driven biometric identification more viable for large-scale security applications.

Despite these advancements, deep learning-based biometric systems come with trade-offs. Computational complexity is a major concern, as training and real-time inference require high processing power. GPUs and TPUs alleviate some of these challenges, but energy consumption remains a critical issue, particularly for mobile and embedded biometric systems. Furthermore, deep learning models require vast labeled datasets to achieve high accuracy, posing challenges in data collection and annotation. Ethical and privacy concerns surrounding biometric data storage and usage also highlight the need for secure and transparent biometric systems.

Overall, deep learning has significantly improved the accuracy, reliability, and adaptability of biometric identification systems. While challenges remain, including computational efficiency, security vulnerabilities, and privacy concerns, advancements in deep learning are paving the way for more secure, scalable, and intelligent biometric authentication solutions. These findings reinforce the role of deep learning in shaping the future of identity verification and security systems.



DISCUSSION

The integration of deep learning into biometric identification has significantly enhanced accuracy, efficiency, and adaptability compared to traditional methods. This study demonstrates that deep learning models consistently outperform conventional biometric techniques across various modalities, including facial recognition, fingerprint identification, iris scanning, and voice recognition. However, despite these advancements, deep learning introduces challenges related to computational demands, data security, and ethical considerations. This discussion examines the impact of deep learning on biometric systems, highlighting both its advantages and limitations.

One of the most notable contributions of deep learning to biometrics is its ability to automatically extract complex patterns and features from raw biometric data, eliminating the need for manual feature engineering. Traditional approaches rely on handcrafted feature extraction, such as minutiae points in fingerprint recognition or eigenfaces in facial recognition, requiring extensive domain expertise. In contrast, deep learning models, particularly Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), learn hierarchical and high-level representations, leading to improved recognition accuracy and robustness. The study finds that CNN-based models excel in facial, fingerprint, and iris recognition, while RNNs and Long Short-Term Memory (LSTM) networks enhance voice recognition by capturing temporal dependencies in speech data.

Deep learning models also demonstrate greater resilience to variations in biometric data, making them highly suitable for real-world applications. Traditional biometric systems often struggle with factors such as lighting changes, occlusions, pose variations, and background noise. However, deep learning models, trained on large and diverse datasets, generalize better and maintain high performance in uncontrolled environments. For example, deep learning-based facial recognition systems in this study maintain high accuracy despite variations in facial expressions, aging, and partial occlusions. Similarly, fingerprint and iris recognition models trained on augmented datasets show robustness against noise and distortions, surpassing the effectiveness of traditional handcrafted feature-based techniques.

Another major advantage of deep learning in biometrics is its ability to detect and counter spoofing attacks. Biometric authentication systems are vulnerable to threats such as facial spoofing, fingerprint replication, and synthetic voice attacks. Traditional methods often fail to distinguish between genuine and fraudulent biometric samples. Deep learning models, particularly those utilizing Generative Adversarial Networks (GANs) and adversarial training, improve security by identifying subtle inconsistencies in spoofed biometric data. This study finds that deep learning-based liveness detection methods effectively differentiate real biometric inputs from fake ones, enhancing the security of authentication systems against presentation attacks.

Despite these strengths, deep learning-based biometric systems face significant computational challenges. Training such models demands substantial computational resources, including high-performance GPUs and TPUs, which may not be practical for all applications, especially those requiring real-time processing or mobile deployment. The study highlights that while deep learning achieves superior accuracy, it comes at the cost of increased processing time and energy consumption. Techniques such as model pruning, quantization, and knowledge distillation help optimize deep learning models, making them more efficient for real-world biometric applications.

Concerns related to data privacy and ethics also arise in deep learning-driven biometric identification. Unlike traditional methods that rely on predefined feature sets, deep learning models require vast amounts of labeled biometric data for training, raising concerns about data collection, storage, and potential misuse. This study underscores the importance of secure data handling measures, including encryption, differential privacy, and federated learning, to protect biometric data from breaches and unauthorized access. Additionally, ethical concerns regarding mass surveillance and bias in biometric recognition systems must be addressed. Deep learning models trained on biased datasets risk exhibiting discriminatory behavior, leading to unfair identification outcomes. Ensuring diversity in training data and incorporating bias-mitigation strategies is crucial for developing fair and ethical biometric systems.

Another limitation of deep learning in biometrics is its vulnerability to adversarial attacks. Unlike traditional techniques with fixed feature extraction rules, deep learning models are highly sensitive to small perturbations in input data. Adversarial attacks, which involve subtle modifications to biometric inputs, can mislead deep learning models, resulting in incorrect identifications. The study finds that while deep learning enhances biometric security in various ways, it also introduces new vulnerabilities that require robust countermeasures. Strategies such as adversarial training, anomaly detection, and ensemble learning are explored as potential solutions to enhance the resilience of deep learning-based biometric systems against adversarial threats.

A comparative analysis between traditional and deep learning-based biometric techniques highlights the transformative impact of artificial intelligence on security and authentication. While conventional methods remain useful for certain applications, deep learning offers unmatched advantages in accuracy, adaptability, and security. However, addressing challenges related to computational efficiency, data privacy, ethical concerns, and adversarial robustness is essential to fully harness the benefits of deep learning in biometric identification.

Overall, this study emphasizes the potential of deep learning to revolutionize biometric authentication while acknowledging the need for continued research and innovation to overcome its limitations. As deep learning algorithms advance and computational hardware becomes more efficient, biometric authentication systems will continue to improve in security, scalability, and accessibility. The findings of this study contribute to the growing body of knowledge in biometric security, highlighting the role of deep learning in shaping the future of identity verification and authentication.

CONCLUSION

Biometric identification has been transformed by deep learning, which surpasses conventional techniques in terms of accuracy, efficiency, and security. It makes autonomous feature extraction possible, increasing flexibility in response to changes in the real world. While spoofing attacks are thwarted by deep learning-based security measures, CNNs and RNNs improve recognition performance. High processing requirements, worries about data privacy, and susceptibility to hostile attacks are obstacles, nevertheless. Attention must also be paid to ethical concerns including partiality and misuse. Future developments must to concentrate on creating models that are effective, safe, and equitable while putting legal frameworks in place to guarantee responsible use. The future of identity verification will be shaped by the ongoing evolution of biometric authentication.

REFERENCE

[1] *Jain, A.K.; Ross, A.A.; Nandakumar, K. Introduction to Biometrics; Springer Science & Business Media: Berlin, Germany, 2011; ISBN 9780387773254.*

[2] *Lumini, A.; Nanni, L. Overview of the combination of biometric matchers. Inf. Fusion* ***2017****, 33, 71–85.*

[3] *Shaheed, K.; Liu, H.; Yang, G.; Qureshi, I.; Gou, J.; Yin, Y. A systematic review of finger vein recognition techniques. Informatics* ***2018****, 9, 213.*

[4] *Oloyede, M.; Hancke, G. Unimodal and Multimodal Biometric Sensing Systems: A Review. IEEE Access* ***2016****, 4, 7532–7555.*

[5] *Bouzouina, Y.; Hamami, L. Multimodal biometric: Iris and face recognition based on feature selection of iris with GA and scores level fusion with SVM. In Proceedings of the 2017 2nd International Conference on Bio-Engineering for Smart Technologies, Paris, France, 30 August–1 September 2017; pp. 1–7.*

[6] *Hezil, N.; Boukrouche, A. Multimodal biometric recognition using human ear and palmprint. IET Biom.****2017****, 6, 351–359.*

[7] *Veluchamy, S.; Karlmarx, L.R. System for multimodal biometric recognition based on finger knuckle and finger vein using feature-level fusion and k-support vector machine classifier. IET Biom.* ***2017****, 6, 232–242.*

[8] *Chanukya, P.S.V.V.N.; Thivakaran, T.K. Multimodal biometric cryptosystem for human authentication using fingerprint and ear. Multimed. Tools Appl.* ***2020****, 79, 659–673.*

[9] *Ammour, B.; Boubchir, L.; Bouden, T.; Ramdani, M. Face–iris multimodal biometric identification system. Electronics* ***2020****, 9, 85.*

[10] *Zhang, Q.; Yang, L.T.; Chen, Z.; Li, P. A survey on deep learning for big data. Inf. Fusion* ***2018****, 42, 146–157.*

[11] *Panasiuk, P.; Szymkowski, M.; Marcin, D. A Multimodal Biometric User Identification System Based on Keystroke Dynamics and Mouse Movements. In Proceedings of the 15th IFIP TC 8 International Conference on Computer Information Systems and Industrial Management, Vilnius, Lithuania, 14–16 September 2016;pp. 672–681.*

[12] *Ding, C.; Member, S.; Tao, D. Robust Face Recognition via Multimodal Deep Face Representation. IEEE Trans. Multimed.* ***2015****, 17, 2049–2058.*

[13] *Al-Waisy, A.S.; Qahwaji, R.; Ipson, S.; Al-Fahdawi, S.; Nagem, T.A.M. A multi-biometric iris recognition system based on a deep learning approach. Pattern Anal. Appl.* ***2018****, 21, 783–802.*

[14] *Al-Waisy, A.S.; Qahwaji, R.; Ipson, S.; Al-Fahdawi, S. A multimodal biometrie system for personal identification based on deep learning approaches. In Proceedings of the 2017 Seventh International Conference on Emerging Security Technologies, Canterbury, UK, 6–8 September 2017; pp. 163–168.*

[15] *Soleymani, S.; Dabouei, A.; Kazemi, H.; Dawson, J.; Nasrabadi, N.M. Multi-Level Feature Abstraction from Convolutional Neural Networks for Multimodal Biometric Identification. In Proceedings of the 2018 24th International Conference on Pattern Recognition, Beijing, China, 20–24 August 2018; pp. 3469–3476.*

[16] *Soleymani, S.; Torfi, A.; Dawson, J.; Nasrabadi, N.M. Generalized Bilinear Deep Convolutional Neural Networks for Multimodal Biometric Identification. In Proceedings of the 2018 25th IEEE International Conference on Image Processing, Athens, Greece, 7–10 October 2018; pp. 763–767.*

[17] *Gunasekaran, K.; Raja, J.; Pitchai, R. Deep multimodal biometric recognition using contourlet derivative weighted rank fusion with human face, fingerprint and iris images. Automatika* ***2019****, 60, 253–265.*

[18] *Kim, W.; Song, J.M.; Park, K.R. Multimodal biometric recognition based on convolutional neural network by the fusion of finger-vein and finger shape using near-infrared (NIR) camera sensor. Sensors* ***2018****, 18, 2296.*

[19] *Liu,W.; Li,W.; Sun, L.; Zhang, L.; Chen, P. Finger vein recognition based on deep learning. In Proceedings of the 2017 12th IEEE Conference on Industrial Electronics and Applications, Siem Reap, Cambodia, 18–20 June 2017; pp. 205–210.*

[20] *Boucherit, I.; Zmirli,M.O.; Hentabli, H.; Rosdi, B.A. Finger vein identification using deeply-fused Convolutional Neural Network. J. King Saud Univ. Comput. Inf. Sci.* ***2020****.*

[21] *Jürgen Schmidhuber Deep learning in neural networks: An overview. Neural Networks* ***2015****, 61, 85–117.*

[22] *Chollet, F. Deep Learning with Python; Manning Publications: New York, NY, USA, 2018; ISBN 9781937785536.*

[23] *Nguyen, K.; Fookes, C.; Ross, A.; Sridharan, S. Iris Recognition with O_-the-Shelf CNN Features: A Deep Learning Perspective. IEEE Access* ***2017****, 6, 18848–18855.*

[24] *Alay, N.; Al-Baity, H.H. A Multimodal Biometric System for Personal Verification Based on Di_erent Level Fusion of Iris and Face Traits. Biosci. Biotechnol. Res. Commun.* ***2019****, 12, 565–576.*

[25] *Yin, Y.; Liu, L.; Sun, X. SDUMLA-HMT: A multimodal biometric database. In Proceedings of the Chinese Conference on Biometric Recognition, Beijing, China, 3–4 December 2011; Volume 7098, pp. 260–268.*

[26] *Kumar, A.; Passi, A. Comparison and combination of iris matchers for reliable personal authentication. Pattern Recognit.* ***2010****, 43, 1016–1026.*